



Situation Awareness & Decision-making for Autonomous Driving

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Situation Awareness & Decision-making for Autonomous Driving

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Keynote talk, IROS 2019 Cutting Edge Forum on “Robotics, AI and ITS contributions to Autonomous Driving”

IROS 2019, Macau, China, November 5th 2019

Technology status & Ongoing challenges for AVs

- Strong involvement of Car Industry & GAFA + Large media coverage + Increasing Governments supports
- An expected market of 515 B€ at horizon 2035 (~17% world automobile market, Consulting agency AT Kearney, Dec 2017)
- But Legal & Regulation issues are still unclear ... idem for Technologies Validation & Certification issues !

=> Numerous experiments in real traffic conditions since 2010 (Disengagement reports & Insights on system maturity)

=> But still insufficient ... Realistic Simulation & Formal methods are also under development (e.g. EU Enable-S3)



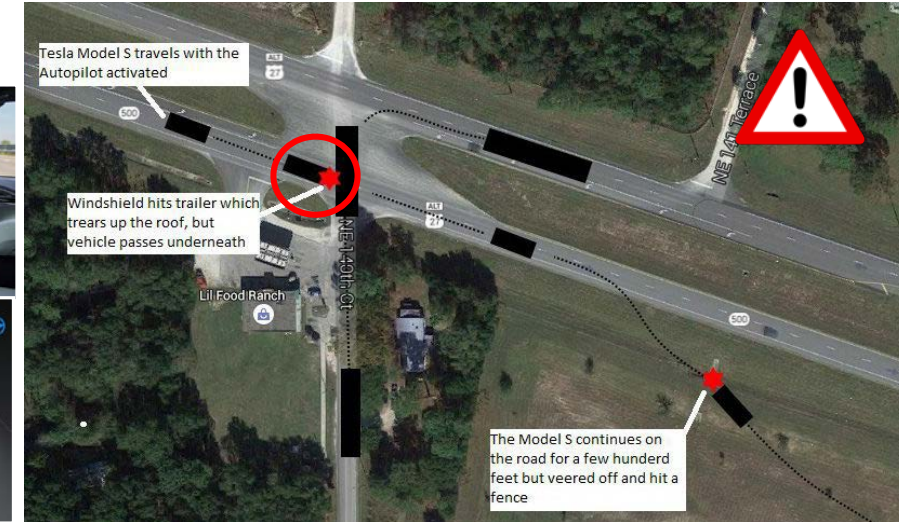
“Self-Driving Taxi Service L3” testing in US (Uber, Waymo) & Singapore (nuTonomy)
=> **Autonomous Mobility Service**, Numerous Sensors + “Safety driver” during testing (take over in case)
=> **Uber**: System testing since 2017, Disengagement every 0.7 miles in 2017 (improved now)
=> **Waymo**: 1st US Self Driving Taxi Service launched in Phoenix in Dec 2018
=> Disengagement reports provide insights on the technology maturity

Millions of miles driven since 2010 (Google, Tesla, Waymo, Uber...)
Several benign & serious accidents in past few years
Safety is still not guaranteed!

Fatal accidents involving AVs – *Perception failure*

- ❑ Tesla driver killed in a crash with Autopilot “level 2” active (*ADAS mode*) – May 2016

- ✓ *The Autopilot failed to detect a white moving truck, with a brightly lit sky (Camera Mobileye + Radar)*
- ✓ *The human driver was not vigilant & didn't took over*



- ❑ Self-driving Uber L3 vehicle killed a woman
=> *First fatal crash involving a pedestrian*
Tempe, Arizona, March 2018

- ✓ *Despite the presence of multiple sensors (lidars, cameras ...), the perception system failed to detect the pedestrian & didn't disengaged*
- ✓ *The Safety Driver reacted too lately (1s before the crash)*



AVs have to face two main challenges

Challenge 1: The need for Robust, Self-diagnosing & Explainable **Embedded Perception**



Video source: AutoPilot Review @ youtube.com

Video Scenario:

- *The Tesla perception system failed to detect the barriers blocking the left side route.*
- *The driver has to take over and steer the vehicle away from the blocked route (for avoiding the collision).*

AVs have to face two main challenges

Challenge 2: The need for Understandable **Driving Decisions** (*share the road with human drivers*)

Human drivers actions are determined by a complex set of interdependent factors difficult to model
(e.g. intentions, perception, emotions ...)

⇒ Predicting **human driver behaviors is inherently uncertain**

⇒ AV have to reason about **uncertain intentions** of the surrounding vehicles



The Lexus SUV, fitted with special sensors, struck the public bus on February 14 in Mountain View, California

Video source: The Telegraph

Video scenario:

- Scene observed by the dash cam of a **bus** moving behind the Waymo AV
- Waymo AV is blocked by an obstacle and it decides to execute a left lane change
- The **bus driver** misunderstood the Tesla's intention and didn't yield
- The two vehicles collided

Perception & Decision-making requirements for AVs

Dynamic Scene Understanding & Navigation Decisions



Situation Awareness & Decision-making

- ⇒ Sensing + Prior knowledge + Interpretation
- ⇒ Selecting appropriate Navigation strategy (planning & control)

ADAS & Autonomous Driving



Embedded Perception & Decision-making for Safe Intentional Navigation

Dealing with unexpected events



- Anticipation & Risk Prediction required for avoiding an upcoming collision with "something"**
- ⇒ High reactivity & reflexive actions
 - ⇒ Focus of Attention & Sensing
 - ⇒ Collision Risk estimation + Avoidance strategy

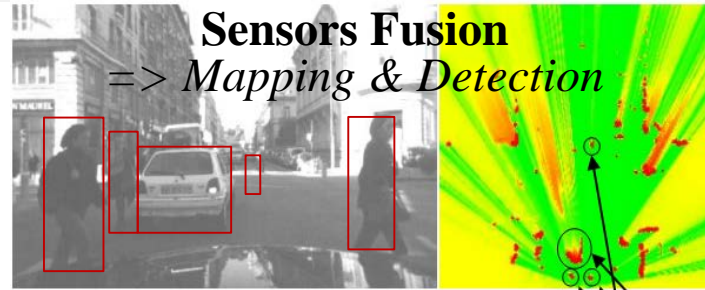
Main features

- ✓ Dynamic & Open Environments ⇒ *Real-time processing & Reactivity (several reasoning levels are required)*
- ✓ Incompleteness & Uncertainty ⇒ *Appropriate Model & Algorithms (probabilistic approaches)*
- ✓ Sensors limitations (no sensor is perfect) ⇒ *Multi-Sensors Fusion*
- ✓ Hardware / Software integration ⇒ *Satisfying Embedded constraints*
- ✓ Human in the loop (mixed traffic) ⇒ *Human Aware Decision-making process (AI based technologies)*
Taking into account Interactions + Behaviors + Social rules (including traffic rules)

1st Paradigm : Embedded Bayesian Perception



Embedded Multi-Sensors Perception
⇒ *Continuous monitoring of the dynamic environment*



❑ Main challenges

- ✓ *Noisy data, Incompleteness, Dynamicity, Discrete measurements*
- ✓ *Strong Embedded & Real time constraints*

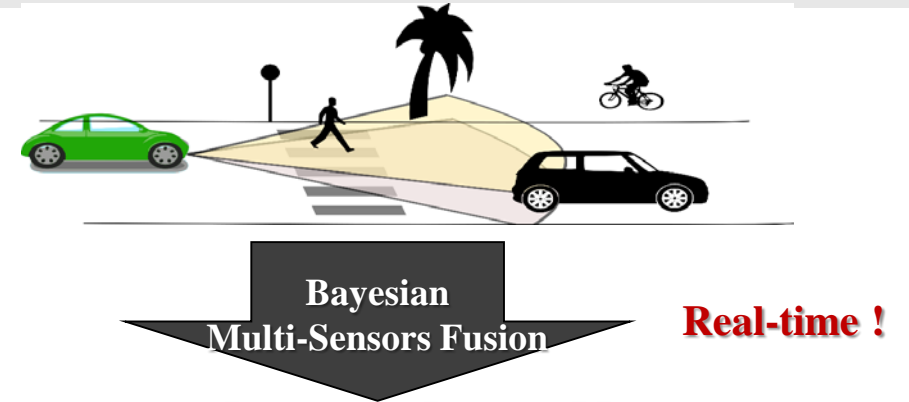
❑ Our Approach: Embedded Bayesian Perception

- ✓ *Reasoning about Uncertainty & Time window (Past & Future events)*
- ✓ *Improving robustness using Bayesian Sensors Fusion*
- ✓ *Interpreting the dynamic scene using Contextual & Semantic information*
- ✓ *Software & Hardware integration using GPU, Multicore, Microcontrollers...*

Bayesian Perception : Basic idea

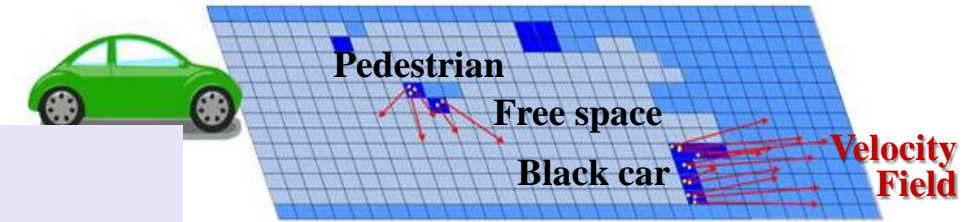
□ Multi-Sensors Observations

Lidar, Radar, Stereo camera, IMU ...



□ Probabilistic Environment Model including Dynamics

$P[o|Z,C] :$ ≈ 0 ≈ 0.5 ≈ 1



Concept of “Dynamic Probabilistic Grid + Bayesian Filtering”

- ⇒ Clear distinction between *Static* & *Dynamic* & *Free* components
- ⇒ Occupancy & Velocity probabilities
- ⇒ Designed for Highly Parallel Processing (to satisfy real-time constraints)
- ⇒ Includes Embedded Models for Motion Prediction & Collision Risk Assessment
- ⇒ Patented technology & Industrial licenses 2018 (Toyota, Easymile)

[PhD Thesis Coué 2005]
[Coué & Laugier IJRR 2005]
[Laugier et al ITSM 2011]
[Rummelhard et al ITSC 2015]
[Mooc uTOP 2015]

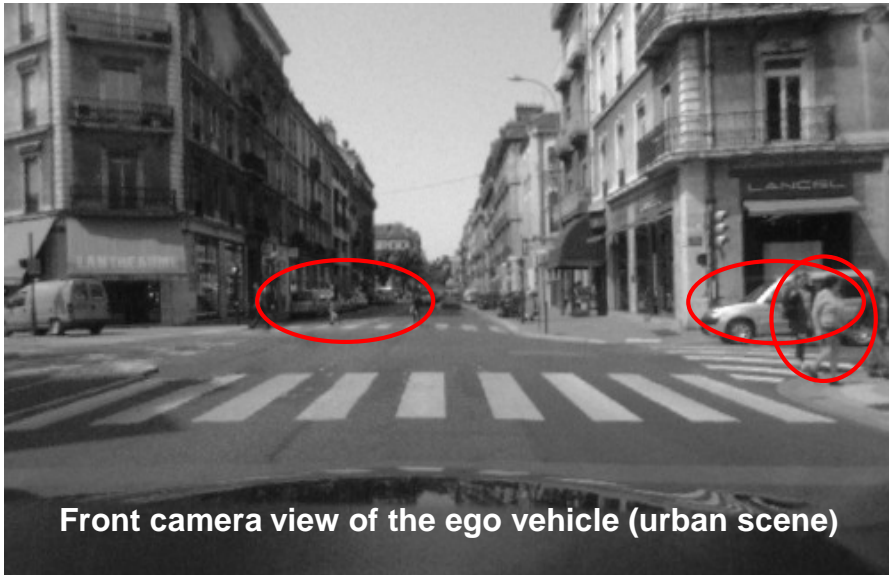
□ Main philosophy

Reasoning at the grid level as far as possible for both :

- *Improving Efficiency & Reactivity to unexpected events* => *Highly parallel processing & High frequency !*
- *Avoiding most of traditional object level processing problems* (e.g. detection errors, wrong data association...)

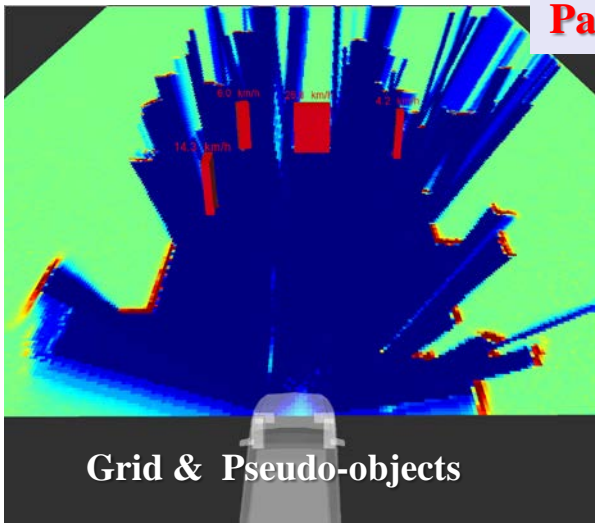
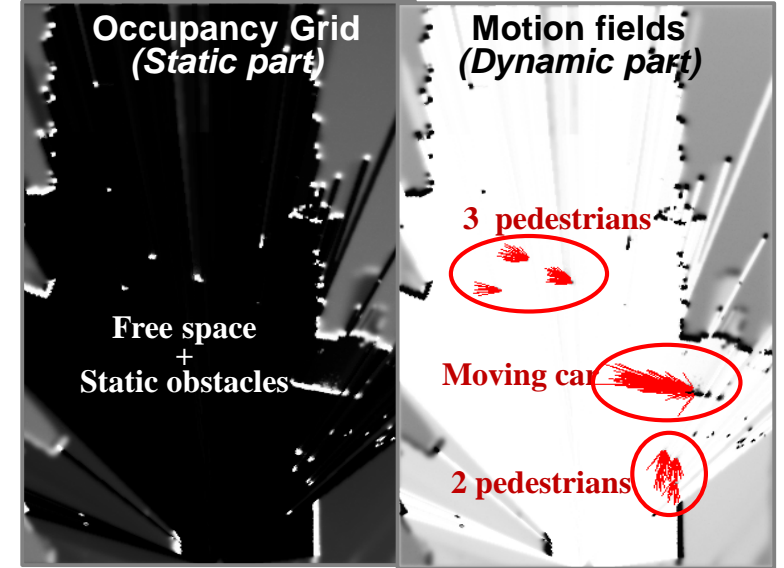
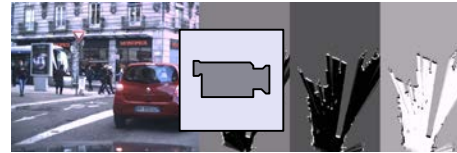
Dynamic Probabilistic Grid & Bayesian Filtering – *Main Features*

=> *Exploiting the dynamic information for a better understanding of the scene*

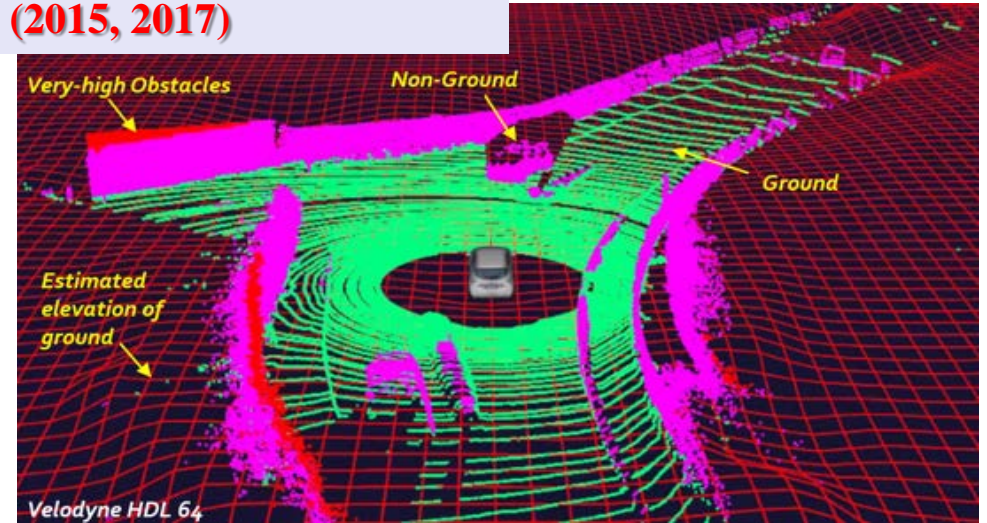


Sensors data fusion
+
Bayesian Filtering
+
Extracted Motion Fields

1st Embedded & Optimized version
(HSBOF, patent 2014)



Patented Improvements & Implementations (2015, 2017)



Detection & Tracking + Moving Objects Classification
=> CMCDOT 2015 (including a “Dense Occupancy Tracker”)

Ground Estimation & Point Cloud Classification
(patent 2017)

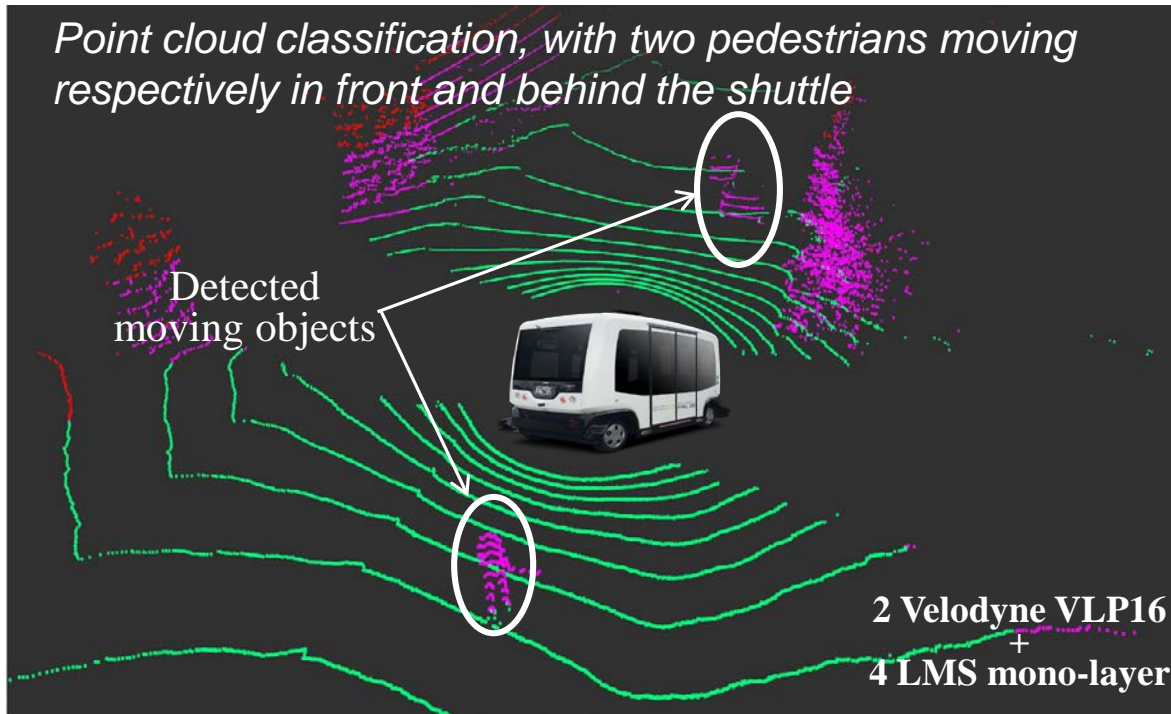
System Integration on a commercial vehicle



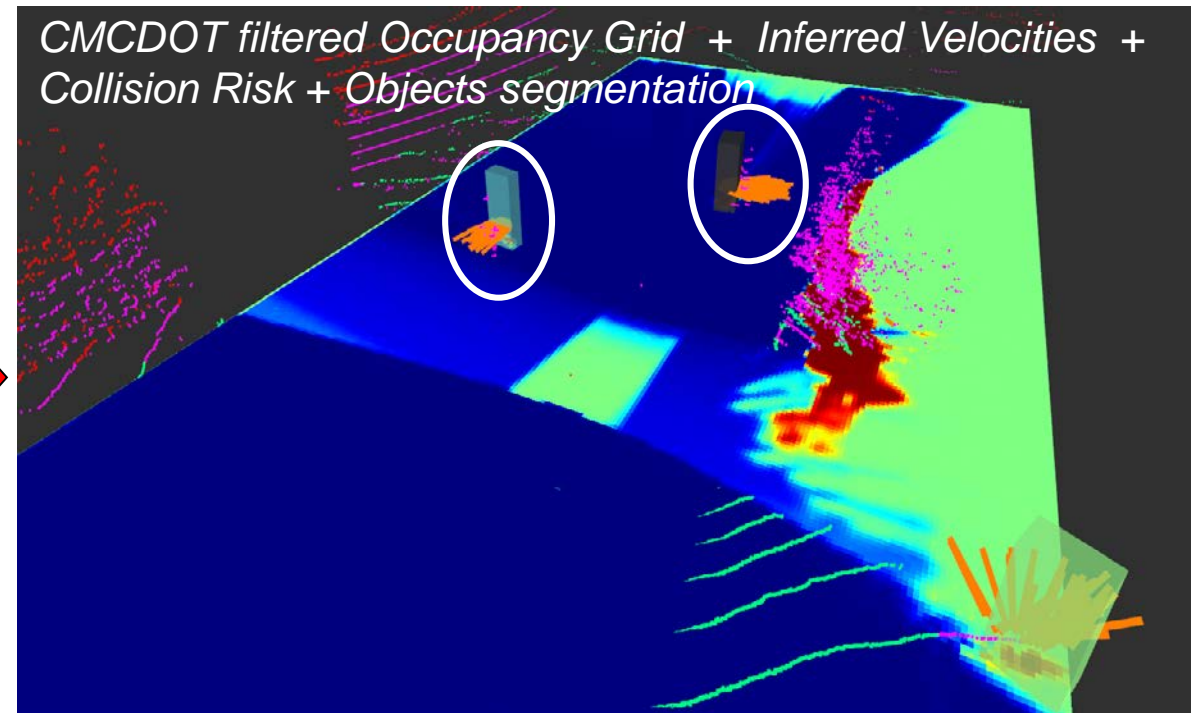
- **POC 2019: Complete system implemented on Nvidia TX1**, and easily connected to the shuttle system network *in a few days* (using ROS)
- **Shuttle sensors data** has been fused and processed in **real-time**, with a successful Detection & Characterization of the **Moving & Static Obstacles**
- **Full integration on a commercial product** under development with an industrial company (confidential)



Point cloud classification, with two pedestrians moving respectively in front and behind the shuttle

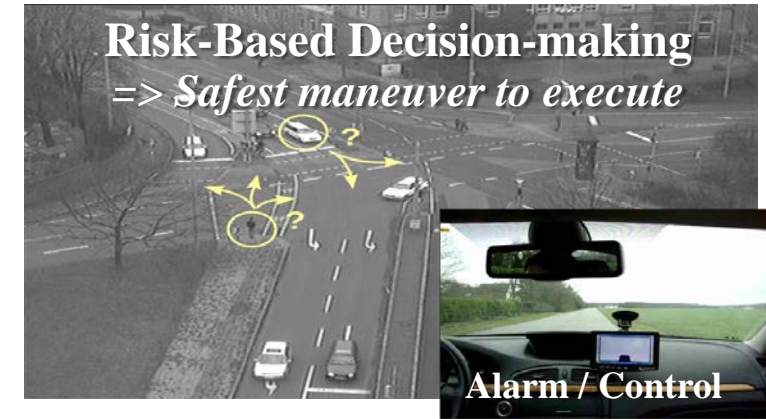
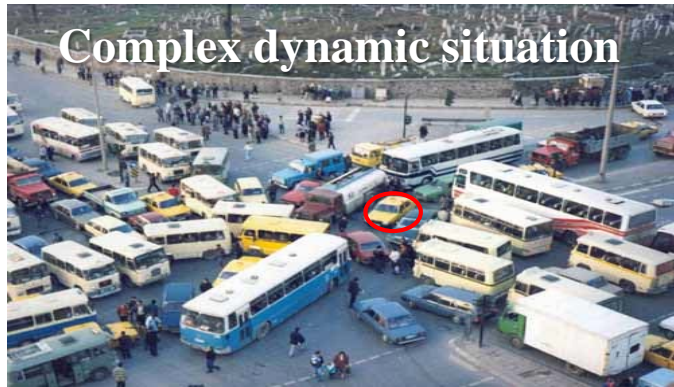


CMCDOT filtered Occupancy Grid + Inferred Velocities + Collision Risk + Objects segmentation



2nd Paradigm: Collision Risk Assessment & Decision-making

=> Decision-making for avoiding Pending & Future Collisions



□ Main challenges

Uncertainty, Partial Knowledge, World changes, Real time

Human in the loop + Unexpected events + Navigation Decision based on Perception & Prior Knowledge

□ Approach: Prediction + Risk Assessment + Bayesian Decision-making

- ✓ Reason about *Uncertainty & Contextual Knowledge* (using **History & Prediction**)
- ✓ Estimate Probabilistic Collision Risk at a given **time horizon** $t+\delta$ (δ = a few seconds ahead)
- ✓ Make Driving Decisions by taking into account the **Predicted behavior** of all the observed surrounding traffic participants (cars, cycles, pedestrians ...) & **Social / Traffic rules**

□ Decision-making: Two types of “collision risk” have to be considered

- ✓ **Short-term collision risk** => *Imminent collisions with “something” (unclassified), time horizon <3s, conservative hypotheses*
- ✓ **Long-term collision risk** => *Future potential collisions, horizon >3s, Context + Semantics, Behavior models*

Concept 1: Short-term collision risk (*Basic idea*)

=> *How to deal with unexpected & unclassified events (i.e. “something” is moving ahead) ?*

=> *Exploit previous observations for anticipating future objects motions & related potential future collision*

Autonomous
Vehicle (Cycab)



Parked Vehicle
(occultation)

**Pioneer Results
(2005)**

*[PhD Thesis C. Coué 2004]
[Coué & Laugier & al IJRR 05]*

Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle “anticipates” the pedestrian motion and brakes (*even if the pedestrian is temporarily hidden by the parked vehicle*)

Short-term collision risk – *Main Features & Results*

=> *Grid level & Conservative motion hypotheses (proximity perception)*

Proximity perception: $d < 100\text{m}$ and $t < 5\text{s}$

$\delta = 0.5\text{s}$ => Precrash

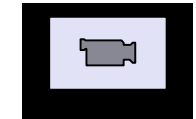
$\delta = 1\text{s}$ => Collision mitigation

$\delta > 1.5\text{s}$ => Warning / Emergency Braking

□ Main Features

- Detect “*Upcoming potential Collisions*” a few seconds ahead (3-5s) in the *Dynamic Grid*
- Risky situations are *both localized in Space & Time* (under conservative motion hypotheses)
- Resulting information is used for choosing the most appropriate *Collision Avoidance Maneuvers*

□ Experimental results



Collision Risk Assessment (video 0:45)

- **Yellow** => time to collision: 3s
- **Orange** => time to collision: 2s
- **Red** => time to collision: 1s

Concept 2: Long-term Collision Risk (*Object level*)

=> *Increasing time horizon & complexity using Context & Semantics*

=> *Key concepts: Behaviors Modeling & Prediction + Traffic Participants Interactions*

Decision-making in complex traffic situations

- ✓ *Understand the current traffic situation & its likely evolution*
- ✓ *Evaluate the Risk of future collision by reasoning on traffic participants Behaviors*
- ✓ *Takes into account Context & Semantics*

*Highly structured environment & Traffic rules
make Prediction more easy*

Context & Semantics

History + Space geometry + Traffic rules

+

Behavior Prediction & Interactions

*For all surrounding traffic participants
(using learned models)*

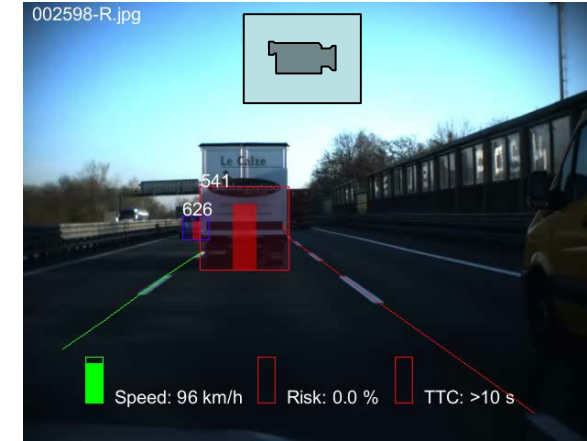
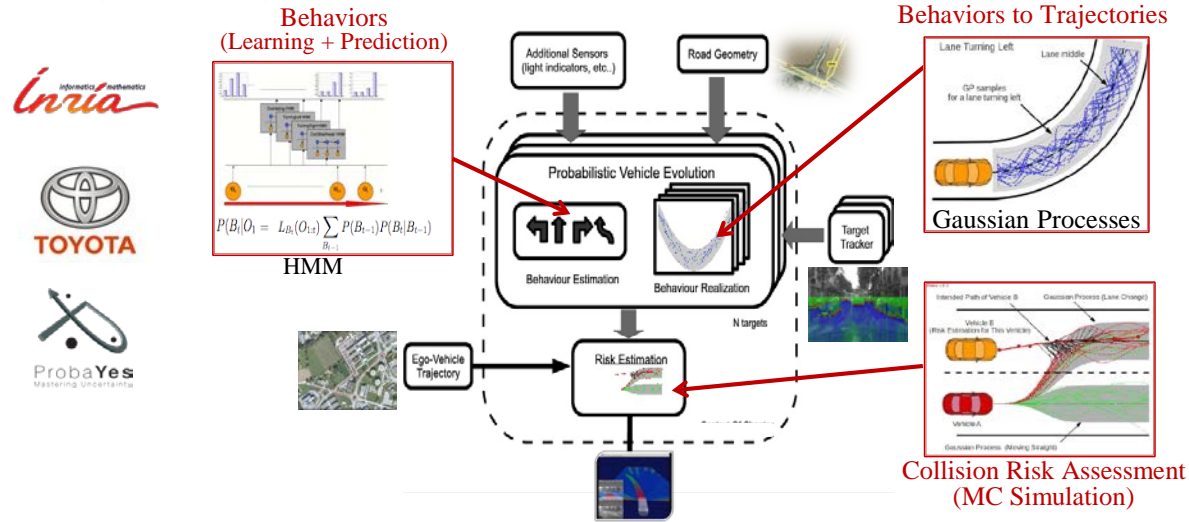
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Probabilistic Risk Assessment

Behavior-based Collision risk – *Main approaches & Results*

=> *Increased time horizon & complexity + Reasoning on Behaviors & Interactions*

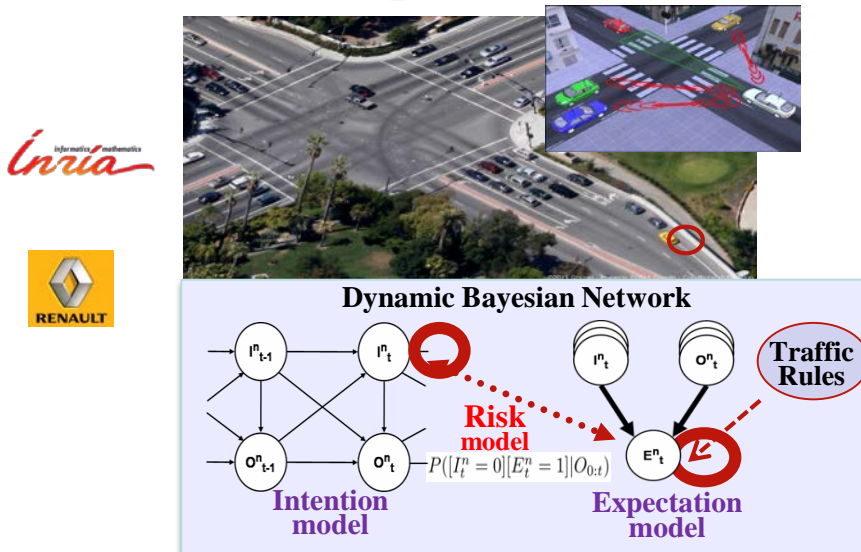
□ Trajectory prediction & Collision Risk => *Patent 2010 (Inria, Toyota, Probayes)*



*Cooperation still on-going
(R&D contracts + PhD)*

Courtesy
Probayes

□ Intention & Expectation (Mixed Traffic & Interactions) => *Patents 2012 (Inria - Renault) & 2013 (Inria - Berkeley)*



**Human-like
reasoning**



*Cooperation still on-going
(R&D contracts + PhD)*

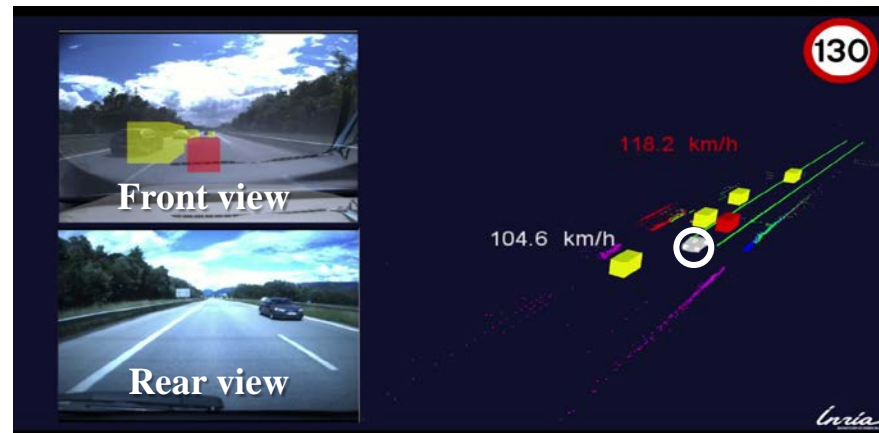
3rd Paradigm: Models improvements using Machine Learning

□ Perception level: *Construct “Semantic Grids” using Bayesian Perception & DL*



□ Decision-making level: *Learn driving skills for Autonomous Driving*

- ❖ *1st Step: Modeling Driver Behavior using Inverse Reinforcement Learning (IRL)*
- ❖ *2nd Step: Predict motions of surrounding vehicles & Make Driving Decisions for Ego Vehicle*

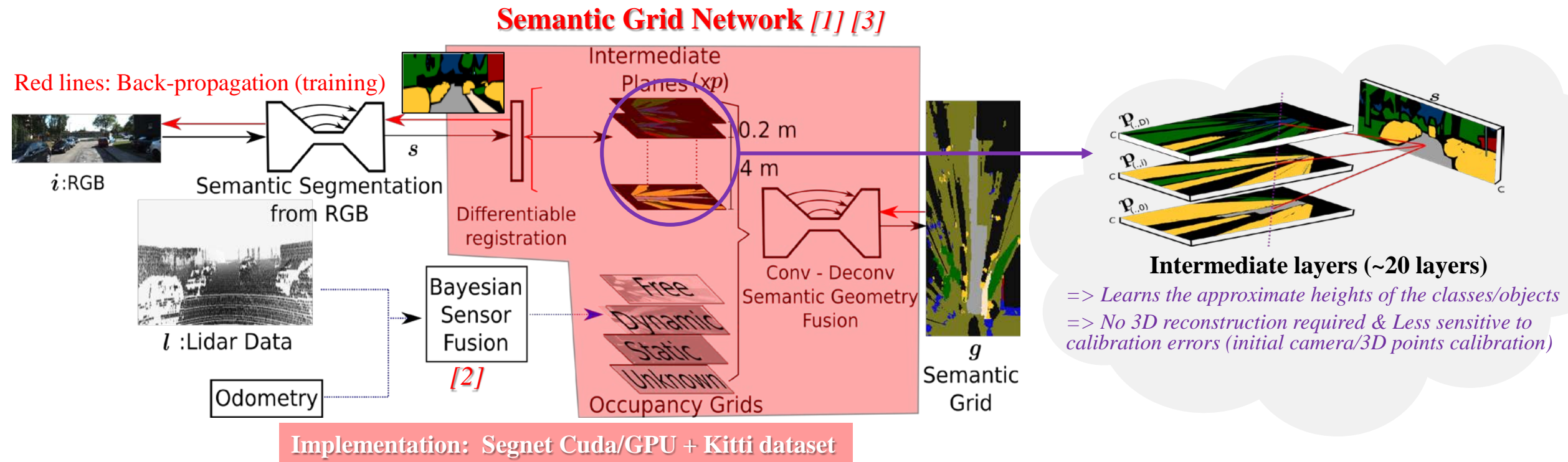


Perception Level: Semantic Grids (Bayesian Perception + DL)

Objective: Add *Semantic information* (cars, pedestrians, roads, buildings...) in each cell of the Dynamic Occupancy Grid model, by exploiting *additional RGB inputs*

Approach: A new “*Hybrid Sensor Fusion approach*” combining *Bayesian Perception & Deep Learning*

[1] [2] + Patent 2019 (Inria, Toyota)

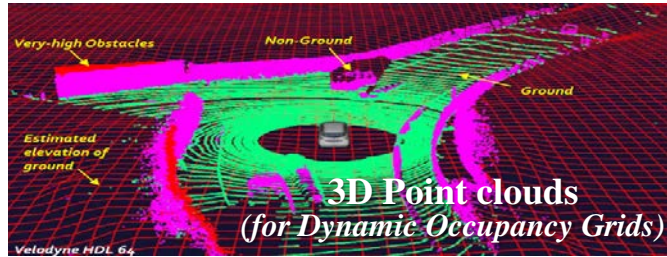


[1] Semantic grid estimation with a Hybrid Bayesian and Deep Neural Network approach, O. Erkent et al., IEEE IROS 2018

[2] Conditional Monte Carlo Dense Occupancy Tracker, Rummelhard et al., ITSC 2015

[3] Segnet: A deep convolutional encoder-decoder architecture for image segmentation, Badrinarayanan et al., IEEE PAMI 39(12) 2017

Semantic Grids – *Experimental Evaluation Approach*



Frontal View (RGB camera)



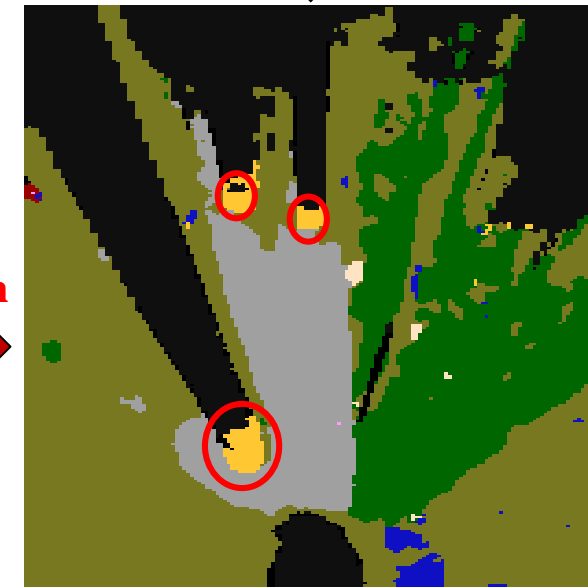
Frontal View Ground-Truth
=> labelled by humans in datasets

Hybrid Sensor Fusion approach (Semantic Grid construction)



Bird's Eye View Ground-Truth
=> Frontal View GT “projected” using
Point-Cloud (Bayesian Perception)
=> Densified by humans (point-clouds
and images have different resolutions)

Comparison

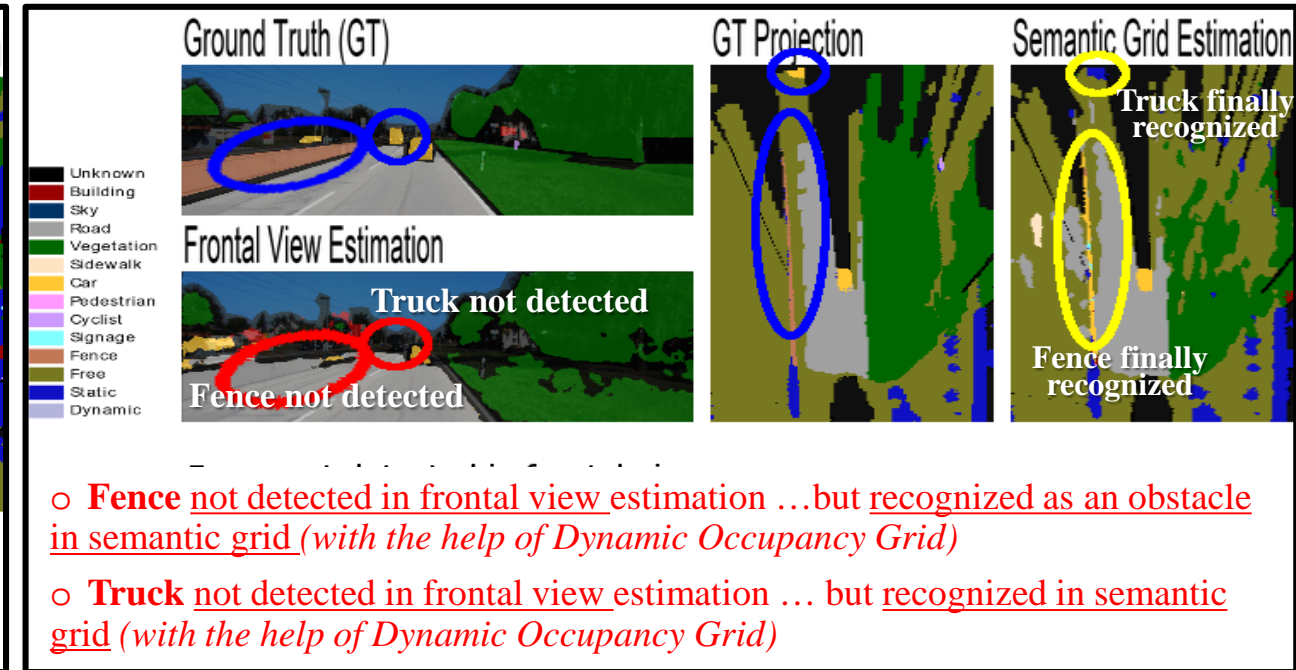
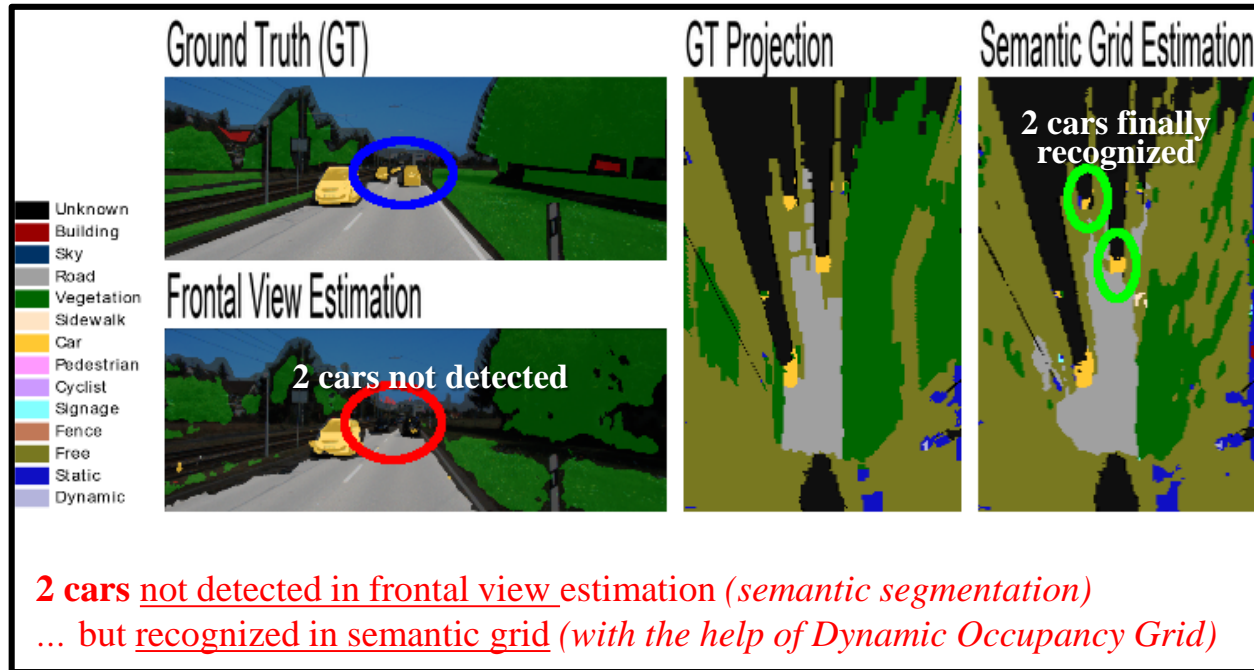


Semantic Grid Prediction
=> Dense structure obtained using
hybrid integration

Unknown
Building
Sky
Road
Vegetation
Sidewalk
Car
Pedestrian
Cyclist
Signage
Fence
Free
Static
Dynamic

Labels

Semantic Grids – *Experimental Results & Current work*



Current Work

- Improve accuracy with more dense training datasets
- Implementation on embedded systems for real-time process
- Adaptation to bad weather conditions
- Panoptic segmentation & tracking



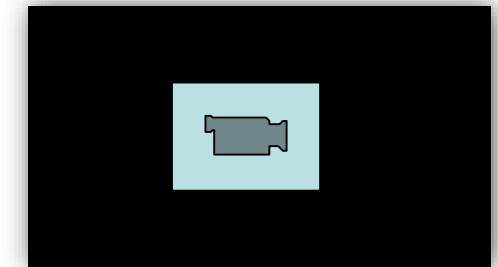
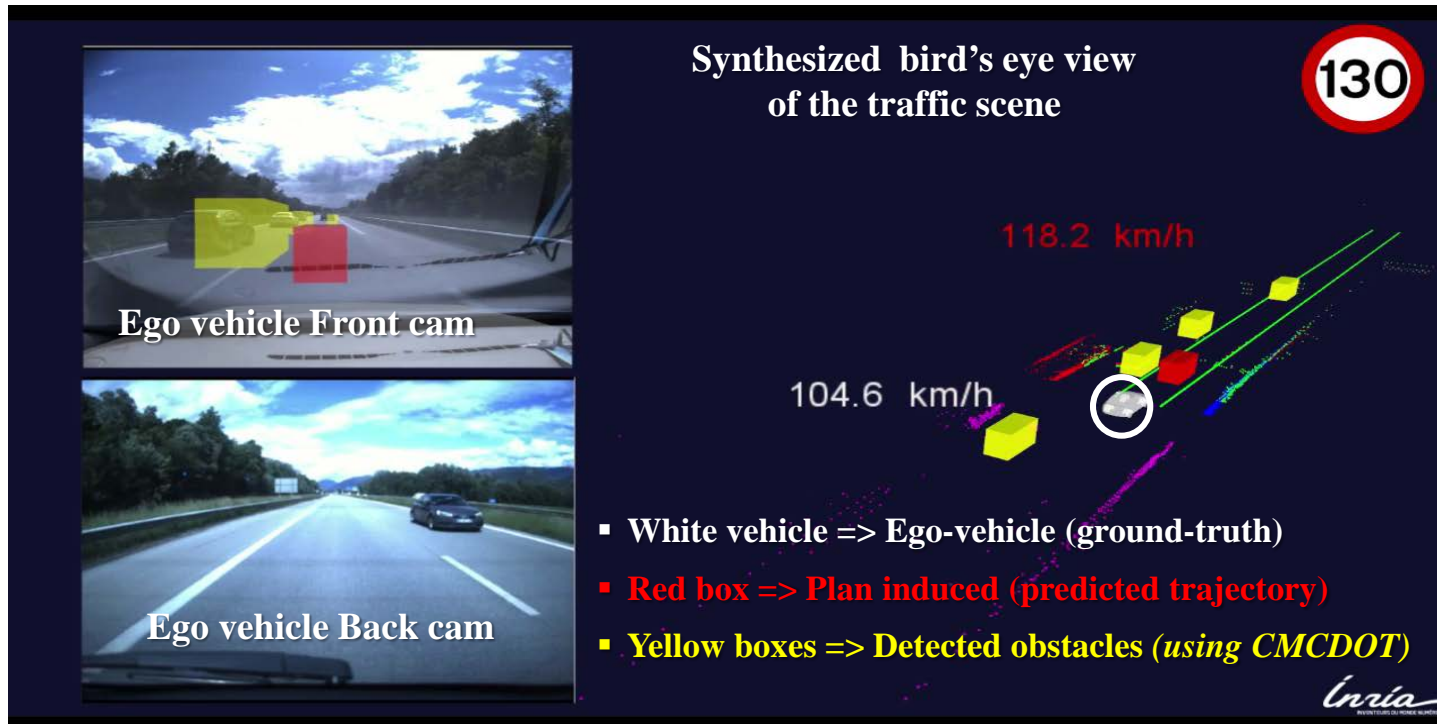
Decision-making level: Learning Driving Skills for AD

1st Step: Driver behavior modeling

[Sierra Gonzalez et al, ICRA 2018]

- Learn Model parameters from real driving demonstrations using *Inverse Reinforcement Learning (IRL)*
- Driver behaviors are modelled using a Cost function $\mathcal{C}(s) = \sum_{i=1}^K w_i \cdot f_i(s)$ which is assumed linear on a set of **K hand-crafted features** (e.g. *Lane index preferences, Deviation from desired velocity, Time-to-collision to frontal targets, Time-gap to rear targets ...*)
- A training set containing “*interesting highway vehicle interactions*” was constructed out of 20 minutes of highway driving data & used to automatically learn the balance between features. *We are extending the approach using larger datasets and various traffic conditions.*

=> Obtained models can be leverage to **Predict human driver behaviors & Generate human-like plans for the ego vehicle** (*mandatory in mixed traffic*)

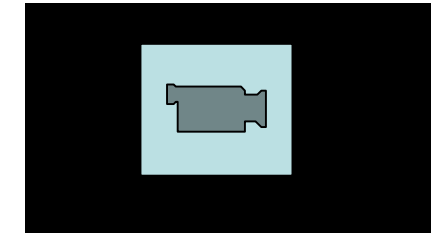
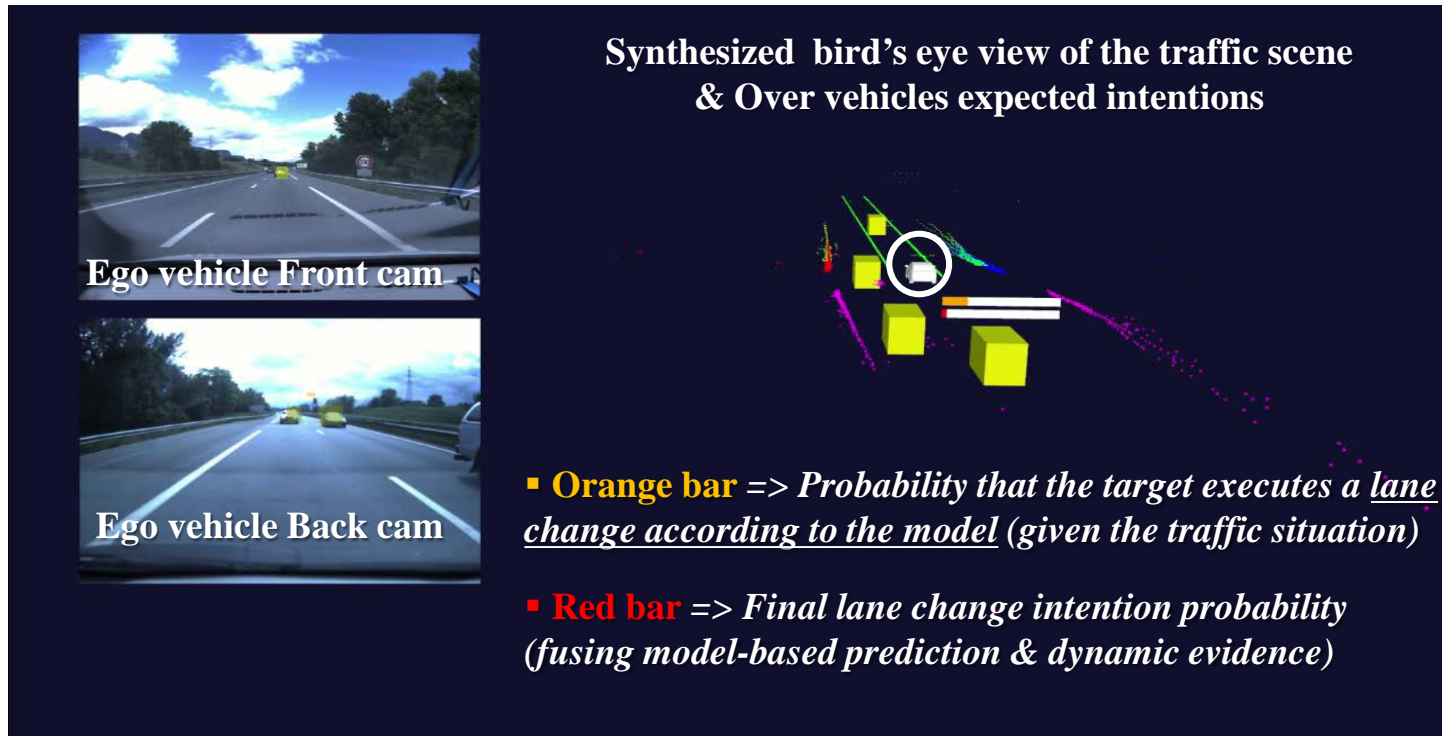


Comparison between demonstrated behavior in test set & behavior induced by the learned model

Decision-making level: Learning Driving Skills for AD

2nd Step: Motion Prediction & Driving Decisions

- A realistic **Human-like Driver Model** can be exploited to **Predict the long-term evolution** (10s and beyond) of traffic scenes [Sierra Gonzalez et al., ITSC 2016]
 - For the **short/mid-term**, both the **Driver model** and the **Dynamics of the target** provide useful information to **determine future driving behaviors**
- => Our **probabilistic model** fuses **Model-based Predictions & Dynamic evidence** to produce robust **lane change intention estimations** in highway scenes [Sierra Gonzalez et al., ICRA 2017]



Comparison between demonstrated behaviors in test set & behaviors induced by the learned model & dynamics evidence

Experimental Vehicles & Connected Perception Units

Toyota Lexus

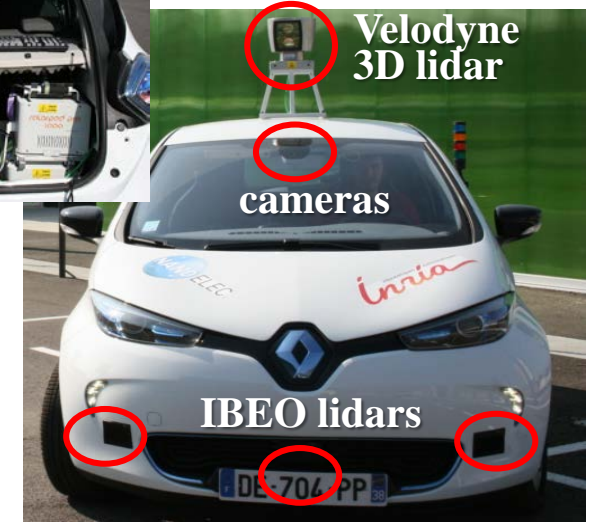


ROS

RT-Maps
under development



Renault Zoé



Connected Perception Unit (V2X communication)

Same embedded perception systems than in vehicles

=> Exchanging only relevant information (e.g. Risk parameters)

Nvidia GTX Titan X
Generation Maxwell



Nvidia GTX Jetson TK1
Generation Maxwell



Nvidia GTX Jetson TX1
Generation Maxwell



Experimental Areas

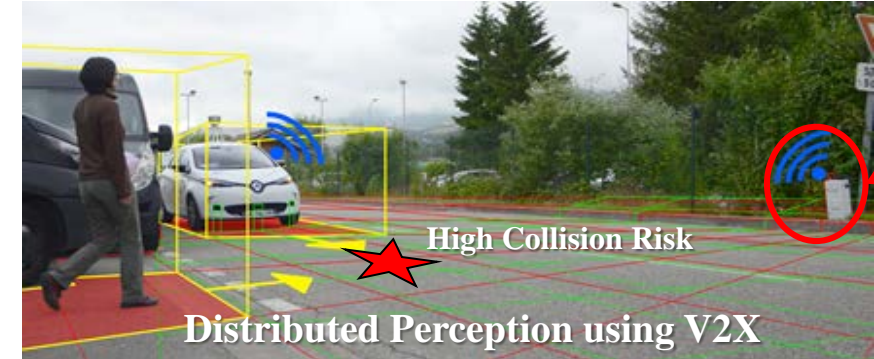
- ❑ Protected experimental area => *Testing Autonomous Driving L3 & L4*



Crash test track



Connected Perception Unit



- ❑ Open real traffic (Urban & Highway) => *Testing Autonomous Driving L2 (ADAS)*



Summary & On going work

□ Autonomous Driving in various Traffic & Context situations (*cooperation with industry*)



Autonomous Shuttles
(~15 km/h, Urban traffic)



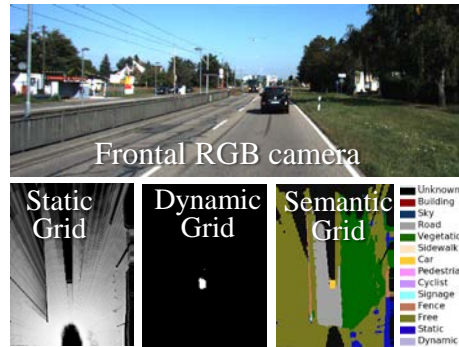
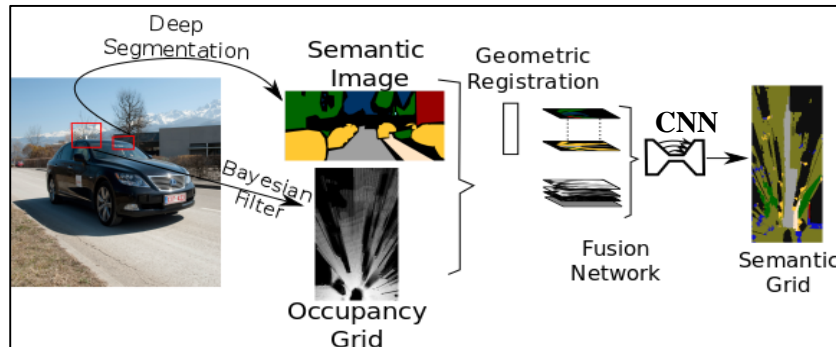
Autonomous Bus (Iveco)
(up to 70 km/h, Urban traffic)



Autonomous Renault Zoe
(up to 70 km/h, Urban traffic)

- Various Dynamics & Motion constraints & Contexts
- Adapted “Collision Risk” & “Collision avoidance maneuvers” (Risk & Maneuver characterization)
- **Cooperation IRT Nanoelec, Renault, Iveco ...**

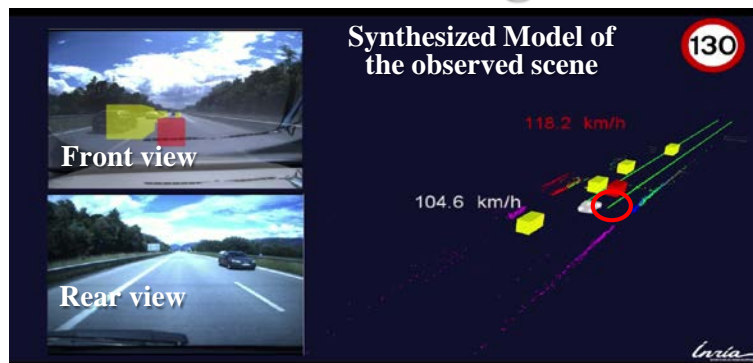
□ Embedded & Extended “Semantic Grids”



- Embedded “Semantic Grids” & “Panoptic Segmentation”
- Improved scene understanding (various weather conditions)
- **Cooperation Toyota**
- 1 Patent & 3 publications (IROS’18, ICARCV’18, Unmanned System journal 2019)

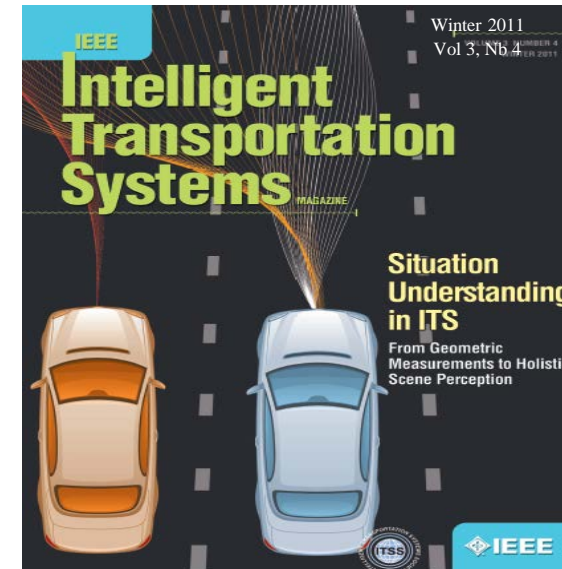
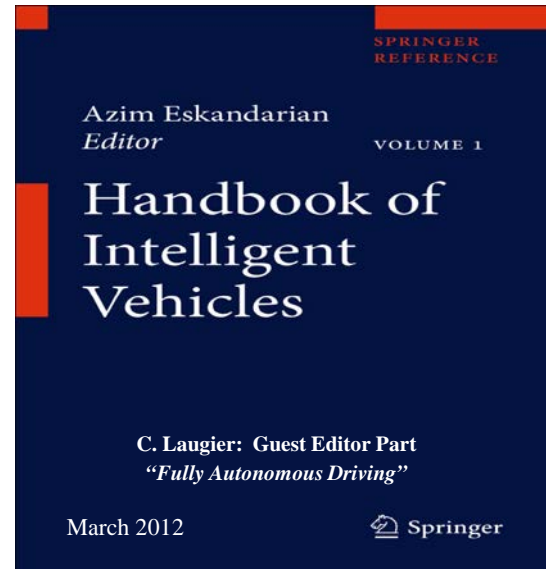
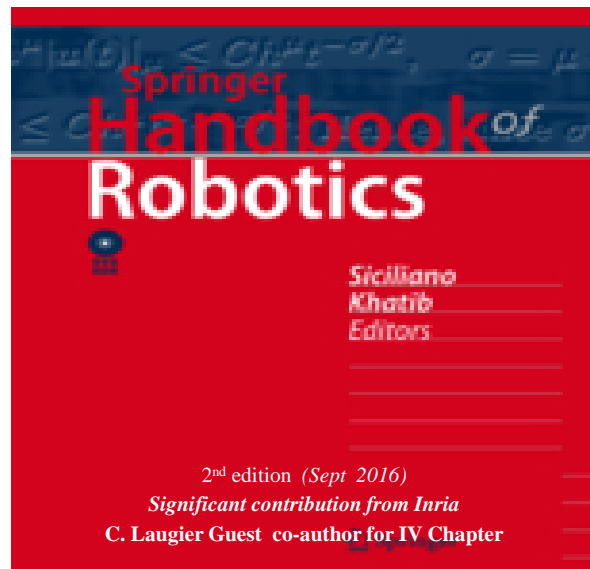


□ Autonomous Driving in mixed traffic (Prediction & Planning) using learned models



- **Driver Behavior modeling** using Driving dataset & Inverse Reinforcement Learning
=> **Human-like Driver Model** (for mixed traffic)
- **Motion Prediction & Driving Decision-making for AD** performed by combining “learned Driver models” & “Dynamic evidences”
- **Cooperation Toyota**
- 2 Patents & 3 publications (ITSC 2016, ICRA 2017, ICRA 2018) & PhD Thesis 2019





Thank You

